

→ Decoder

The decoder is responsible for generating the output sequence one token at a time, using the encoder's output and the previously generated tokens.

Transformer's decoder has 3 main components

① Multi Masked Multi Head Attention

② Multi-head Attention

③ Feed Forward Neural Network

→ Masked Multi Head Attention

Dataset

Eng
 $\langle x_1, x_2, x_3 \rangle$

French
 $\langle y_1, y_2 \rangle$



$\langle y_1, y_2, 0 \rangle \Rightarrow$ output shifted right
↓
zero padding

Input

output

$[4 \ 5 \ 6 \ 7]$

$[1 \ 2 \ 3]$

1- Input Embedding and Positional Encoding

Input output
[4 5 6 7] [1 2 3 0]
 ↓
 4 dimensions

output Embeddings

$[[0.1, 0.2, 0.3, 0.4], [0.5, 0.6, 0.7, 0.8],$
 $[0.9, 1.0, 1.1, 1.2], [0, 0, 0, 0]]$

considering positional encoding to be 0

2- Linear Projection for Q, K, V

Query (Q), Key (K), Value (V)

$$\cancel{Q=K=V} \quad W^Q \Rightarrow W^K \Rightarrow W^V = I$$

$Q = \text{Output Embedding} \times W^Q = \text{Output Embedding}$

$K = \text{Output Embedding} \times W^K = \text{Output Embedding}$

$V = \text{Output Embedding} \times W^V = \text{Output Embedding}$

$$Q = K = V = [[0.1, 0.2, 0.3, 0.4], [0.5, 0.6, 0.7, 0.8],$$
$$[0.9, 1.0, 1.1, 1.2], [0, 0, 0, 0]]$$

3- Scaled Dot Product Attention

$$\text{Score} = \frac{Q \times K^T}{\sqrt{d_k}}$$

$$= \frac{Q \times K^T}{2}$$

$$= \frac{\begin{bmatrix} 0.1 & 0.2 & 0.3 & 0.4 \\ 0.5 & 0.6 & 0.7 & 0.8 \\ 0.9 & 1.0 & 1.1 & 1.2 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0.1 & 0.5 & 0.9 & 0 \\ 0.2 & 0.6 & 1.0 & 0 \\ 0.3 & 0.7 & 1.1 & 0 \\ 0.4 & 0.8 & 1.2 & 0 \end{bmatrix}}{2}$$

2

$$= \begin{bmatrix} 0.3 & 0.7 & 1.1 & 0.0 \\ 0.7 & 1.9 & 3.1 & 0.0 \\ 1.1 & 3.1 & 5.1 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 \end{bmatrix}$$

4- Masked Application

It helps managing the structure of the sequences being processed and ensures the model behaves correctly during training and inference.

> Reasons

- ① Handling variable length sequences with padding MASK.

Purpose

- ① To handle sequences of different length in batch
- ② To ensure the padding tokens, which are added to make sequences of uniform length, do not effect the model prediction.

Example

Input Sequence [1, 2, 3]

Output Sequence [4, 5, 0] 0 is padding token

↳ Influence attention mechanism



lead to incorrect or biased prediction

Masking {
↳ padding mask
↳ look ahead mask

Padding Mask → The tokens are ignored

Look Ahead Mask → Maintain auto regressive properties

↳ to ensure that each position in the decoder output sequence can only attend the previous position, no future position

↳ Seqence → Language Modeling, Translation

Example Padding Mask

$$[4, 5, 0] \xrightarrow{\text{padding mask}} [1, 1, 0]$$

$$\begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Token 1 can attend 1, 2

Token 2 can attend 1, 2

For each token in the sequence, the mask should indicate with token it can attend to

Example Look Ahead Mask

$$[4, 5, 0] \rightarrow \begin{bmatrix} [1 & 0 & 0], \\ [1 & 1 & 0], \\ [1 & 1 & 1] \end{bmatrix}$$

Combine Padding and Look Ahead Mask

$$\text{Combine Mask} = \text{Padding Mask} \cdot \text{Look Ahead Mask}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

wherever in the combined mask, the value is 0, there we specifically specify add -infinity, to zero out the influence when softmax is applied.

> Solving Attention Score with Masking

$$\text{Scores} = \begin{bmatrix} [0.3, 0.7, 1.1, 0.0], [0.7, 1.9, 3.1, 0.0], \\ [1.1, 3.1, 5.1, 0.0], [0.0, 0.0, 0.0, 0.0] \end{bmatrix}$$

Look Ahead Mask

$$\begin{bmatrix} [1 & 0 & 0 & 0] \\ [1 & 1 & 0 & 0] \\ [1 & 1 & 1 & 0] \\ [1 & 1 & 1 & 1] \end{bmatrix}$$

Padding Mask

$$\begin{bmatrix} [1 & 1 & 1 & 0] \\ [1 & 1 & 1 & 0] \\ [1 & 1 & 1 & 0] \\ [0 & 0 & 0 & 0] \end{bmatrix}$$

Combined Mask

$$\text{Combined mask} = \text{Look Ahead} \times \text{Padding}$$

$$= \begin{bmatrix} [1, 0, 0, 0], \\ [1, 1, 0, 0], \\ [1, 1, 1, 0], \\ [1, 1, 1, 0] \end{bmatrix}$$

X

Masked Score

$$\text{Combined mask} = \begin{bmatrix} [1, -\infty, -\infty, -\infty], \\ [1, 1, -\infty, -\infty], \\ [1, 1, 1, -\infty], \\ [1, 1, 1, -\infty] \end{bmatrix}$$

$$\text{Masked Score} = \text{Score} \cdot \text{Combined Mask}$$

$$= \begin{bmatrix} [0.3, -\infty, -\infty, -\infty], \\ [0.7, 0.9, -\infty, -\infty], \\ [1.1, 3.1, 5.1, -\infty], \\ [0.0, 0.0, 0.0, -\infty] \end{bmatrix}$$

Softmax

$$\text{Softmax Score} = \text{Softmax}(\text{Masked Score})$$

$$= \begin{bmatrix} [1.0, 0.0, 0.0, 0.0], \\ [0.3, 0.7, 0.0, 0.0], \\ [0.1, 0.3, 0.6, 0.0], \\ [1.0, 0.0, 0.0, 0.0] \end{bmatrix}$$

Weighted Sum of Values

$$\text{Attention Score} = \text{Softmax Score} \times \text{Value Vector}(V)$$

→ Encoder Decoder Multihead Attention

- ① From encoder output → set of attention vector K and V
- ② Masked multi head → Attention vector Q

These Keys and Values are to be used by each decoder in its "encoder-decoder" attention layer

⇓

helps the decoder to focus on appropriate places in the input sequence

→ Final Linear and Softmax Layer

- ① The linear layer is a simple fully connected neural network that projects the vector produced by the sequence stack of decoder ⇒ Logit vectors

Model ⇒ 10,000 ⇒ Vocabulary ⇒ logit vectors ⇒ 10,000

- ② Softmax layer turn those vector scores into probabilities. The cell/vector with the highest probability is chosen and the word associated with it is produced as the output